INTEGRATING METEOROLOGICAL UNCERTAINTY INTO OPERATIONAL SNOWPACK AND AVALANCHE HAZARD MODELLING: INITIAL EXPLORATIONS IN ENSEMBLE FORECASTING

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ABSTRACT: Snowpack modelling has established itself as a valuable additional source of information for avalanche forecasting. However, translating uncertainty in meteorological inputs into tangible outputs for practitioners remains a challenge. In most operational uses, the required input data is taken from one weather forecast model run (e.g., the HRDPS model in Canada), and the simulations are run in a deterministic mode, producing a single snowpack realization that does not reflect the range of possible snowpack conditions arising from uncertainty in meteorological forcing. Ensemble approaches represent a promising way to address this limitation, as they involve running the model multiple times with slightly perturbed meteorological inputs to explore the range of possible snowpack conditions. While ensemble modelling is widely used in weather forecasting, its application to avalanche forecasting remains limited, in part because the simulations produce immense datasets that are difficult to interpret for operational use. In this pilot study, we explore the use of ensemble approaches for operational avalanche forecasting by examining the effects of perturbations in temperature and precipitation on simulated snowpack stratigraphy and stability. We focus on the 2021/22 winter season at three locations across Canada, where we identify situations involving weak layers to investigate the effects of such perturbations. Our results indicate that even small perturbations can substantially influence the formation and evolution of weak layers, leading in some cases to a wide spread of possible effects that persist throughout the season, while in others their impact remains limited, resulting in more consistent outcomes. Overall, this study highlights how accounting for meteorological input uncertainty can enhance both the interpretation and operational use of snowpack simulations, supporting more robust avalanche forecasting practices. Our approach allows us to estimate uncertainty margins in snowpack stability forecasts, providing an explicit quantification of forecast uncertainty. Moreover, ensemble modeling opens the door to best-member selection strategies, whereby multiple simulations with perturbed meteorological forcing are used to identify the scenario that best aligns with field observations.

KEYWORDS: snowpack modelling; meteorological uncertainty; ensemble modelling; snow stratigraphy; skier triggering

1. INTRODUCTION

Snowpack simulations represent a valuable tool for avalanche forecasters to assess avalanche danger (Morin et al. 2020). Snow cover models, like SNOWPACK (Bartelt and Lehning 2002), are driven with meteorological data from either automatic weather stations or numerical weather prediction models and can reproduce characteristics of the natural snow stratigraphy, such as persistent weak layers and melt-freeze crusts, which are the key to avalanche forecasting (Calonne et al. 2020).

When simulating snowpack evolution, one of the main sources of uncertainty is the weather forecast itself, which is often inaccurate due to the chaotic nature of atmospheric dynamics (Lorenz 1963), the intrinsic errors of mathematical models (Bauer et al. 2015), and the inaccuracy of the initial conditions (Kalnay 2002). As a consequence, deterministic forecasts cannot fully capture the range of possible atmospheric evolutions. Ensemble approaches have proven to be a promising tool to address this limitation in weather forecasting (Gneiting and Raftery 2005). Instead of producing a single forecast representing the most likely atmospheric state (like a deterministic model), ensemble models generate a set of possible forecasts, providing information on the range of plausible future conditions.

In recent years, several studies have investigated the application of ensemble modeling to snow and

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avalanche forecasting. Among the most notable contributions, Vernay et al. (2015) demonstrated that driving snowpack simulations with ensemble weather forecasts significantly improves the reliability of avalanche hazard predictions by accounting for meteorological uncertainty. Focusing on model uncertainty, Lafaysse et al. (2017) developed a multiphysics ensemble framework capable of capturing many of the errors associated with deterministic simulations. Statistical post-processing techniques have also been investigated to improve ensemble forecasts of new snow depth: Nousu et al. (2019) showed that post-processing substantially enhances forecast reliability, while Evin et al. (2021) demonstrated that machine learning-based methods provide additional improvements, particularly for difficult-to-predict snowfall events. More recently, Vernay et al. (2025) developed an ensemble precipitation analysis that combines radar observations, rain gauges, and numerical weather prediction outputs to improve precipitation estimates.

Despite these promising developments, the operational use of ensemble approaches for avalanche forecasting remains limited because of their high computational cost and the large volume of data they generate, which can be challenging to process and interpret in practice. Nevertheless, recent advances are helping to bridge this gap. For example, Herla et al. (2022) presented an algorithm to extract representative information from multiple snowpack simulations, while the development of xsnow (Herla et al. 2025) opened new possibilities for handling multiple simulations for operational use.

This pilot study aims to move ensemble-inspired approaches closer to operational avalanche forecasting. Rather than exploring combinations of simultaneous perturbations, we investigate the effects of controlled and separate perturbations of two key weather variables, air temperature and precipitation (Richter et al. 2020), on snowpack evolution. By isolating the influence of each variable, we aim to better understand their individual contributions while retaining an approach that is both computationally and analytically tractable and can provide information directly relevant to operational avalanche forecasting.

2. METHODS

2.1. Overview of research approach

Our analysis is designed to first provide a general overview of how uncertainties in meteorological forecasts influence snowpack stability throughout an entire winter season. Therefore, the reference meteorological inputs used in this study consist of deterministic weather forecasts rather than observations, allowing us to investigate how forecast uncertainties propagate through snowpack simulations. We aim to identify the typical effects induced by perturbations, the conditions under which they become relevant, and the periods of the season when snowpack stability is most sensitive to changes in meteorological forcing. Building on this general assessment, we then examine specific situations in greater detail. Ultimately, our goal is to identify how controlled perturbation approaches can be useful for operational avalanche forecasting,

2.2. Study sites

We considered three locations across Canada over the 2021/22 winter season: Bow Summit, Glacier National Park, and Whistler. The season 2021/22 was chosen because it was characterized by several atmospheric rivers and widespread instability related to the formation of persistent weak layers. Considering three different locations allowed us to investigate a variety of avalanche climate regimes in Canada: maritime, transitional, and continental (Hägeli and McClung 2003). For each site, daily public avalanche forecasts were available from December 1 to April 15 (Avalanche Canada 2026b), enabling comparisons between our snowpack simulations and field observations.

2.3. Weather data and perturbations

Deterministic hourly weather forecasts were obtained from the High Resolution Deterministic Prediction System (HRDPS; Environment and Climate Change Canada (2026)) and used as the reference meteorological forcing for all simulations. Specifically, Bow Summit data referred to an elevation of 2339 m a.s.l., Glacier National Park to 1529 m a.s.l., and Whistler to 1429 m a.s.l.

Starting from these reference forecasts, we generated a set of controlled perturbations designed to mimic plausible meteorological forecast uncertainty. Rather than introducing random noise, we applied systematic forcing biases, as Raleigh et al. (2015) showed that snowpack evolution is considerably more sensitive to persistent biases in meteorological forcing than to random fluctuations. This difference arises from the systematic nature of biases, which can induce a sustained deviation in snowpack evolution, whereas the effects of random errors tend to compensate for each other.

Table 1: Input uncertainties introduced as bias (b) to air temperature (TA) and precipitation (PSUM).

Variable	Perturbations	Unit	Perturbed variable
TA	-3.0, -2.5, -2.0, -1.5, -1.0, -0.5, +0.5, +1.0, +1.5, +2.0, +2.5, +3.0	°C	$\mathrm{TA}' = \mathrm{TA} + b$
PSUM	-50, -30, -20, -15, -10, -5, +5, +10, +15, +25, +50, +100	%	$\mathrm{PSUM}' = \mathrm{PSUM}(1 + b)$

The perturbation procedure was repeated independently for each day of the winter season. For a given starting day, one of the 24 perturbation listed in Table 1 was selected and applied to the reference forecast. The perturbation affected only one meteorological variable, either air temperature (TA) or precipitation (PSUM), while all other variables remained unchanged. These two variables were selected because previous sensitivity analyses identified them as the dominant sources of meteorological uncertainty affecting snowpack evolution (Richter et al. 2020). Once applied, the perturbation was maintained over the subsequent 4 days of the forecast, starting at 2 p.m. local time on the selected day. Consequently, each simulation differed from the reference simulation only through a single, prescribed bias in either air temperature or precipitation over a 4-day period.

2.4. *Snowpack simulations and skier stability index*

The snow cover model SNOWPACK (version 3.7.0) was run for flat terrain using air temperature, precipitation, relative humidity, wind speed and direction, and incoming shortwave and longwave radiation. Simulations were run from the beginning of the winter season until the end of April to investigate both the immediate and the long-term effects of the imposed perturbations. Since the meteorological forcing was identical prior to the first perturbation, each perturbed simulation was identical to the reference simulation up to that time. Although the perturbations were applied only over a 4-day period, their effects could persist well beyond the perturbation window as the snowpack continued to evolve under identical meteorological forcing. Our analysis therefore focuses on the differences that emerged after the perturbation was introduced and how they evolved throughout the remainder of the season.

To assess skier-snowpack stability from the simulated stratigraphies we exploited the $\mathrm{SK}_{38}^{\mathrm{CCL}}$ index (Borsotti et al. in preparation). In simple terms, when computed for a particular layer, the $\mathrm{SK}_{38}^{\mathrm{CCL}}$ index represents the ratio between the layer's critical crack length and the crack length induced by a skier within that layer. Consequently, values larger than 1 indicate layer stability, while lower than 1 layer (and whole snowpack) instability. We selected the $\mathrm{SK}_{38}^{\mathrm{CCL}}$ index because Borsotti et al. (in preparation) demonstrated that it improves upon the classical skier stability index SK_{38} (Jamieson and Johnston 1998; Monti et al. 2016) while offering several advantages over the widely used P_{unstable} random forest (Mayer et al. 2022). In particular, it provides excellent ability in identifying skier-triggered avalanche conditions and tracking weak layers. The $\mathrm{SK}_{38}^{\mathrm{CCL}}$ index is designed to assess dry-snow stability, as the processes leading to wet-snow instability are different (Mitterer et al. 2013). However, during the periods considered in this study, the simulated snowpacks were generally dry, justifying the use of this index.

3. RESULTS

3.1. *Effects of the perturbations over the season*

We start our analysis focusing on Glacier National Park and considering the entire winter season, to highlight the general effects induced by perturbations on snowpack stability. Figure 1 illustrates the values of the $\mathrm{SK}_{38}^{\mathrm{CCL}}$ index one, two, and three days after the perturbations started. As expected, the deviation from the reference simulation increases with both the duration of the perturbation and the magnitude of the imposed bias. Overall, the index is more sensitive to precipitation than to air temperature, in agreement with the findings of Richter et al. (2020) concerning other stability metrics. The largest effects of the perturbations are observed at the beginning of the season. Thereafter, their influence generally becomes less pronounced, particularly for temperature perturbations. Nevertheless, noticeable deviations associated with precipitation perturbations remain visible during January. As expected, temperature perturbations have the greatest impact when air temperatures are close to 0°C. Obviously, precipitation perturbation are irrelevant in absence of precipitation. Importantly, some perturbations result in a different snowpack stability assessment.

3.2. *Temperature-induced snowmelt after a snowfall*

Consider the Bow Summit study site. A few days before December 1, the season's most significant snowfall occurred, after which temperatures

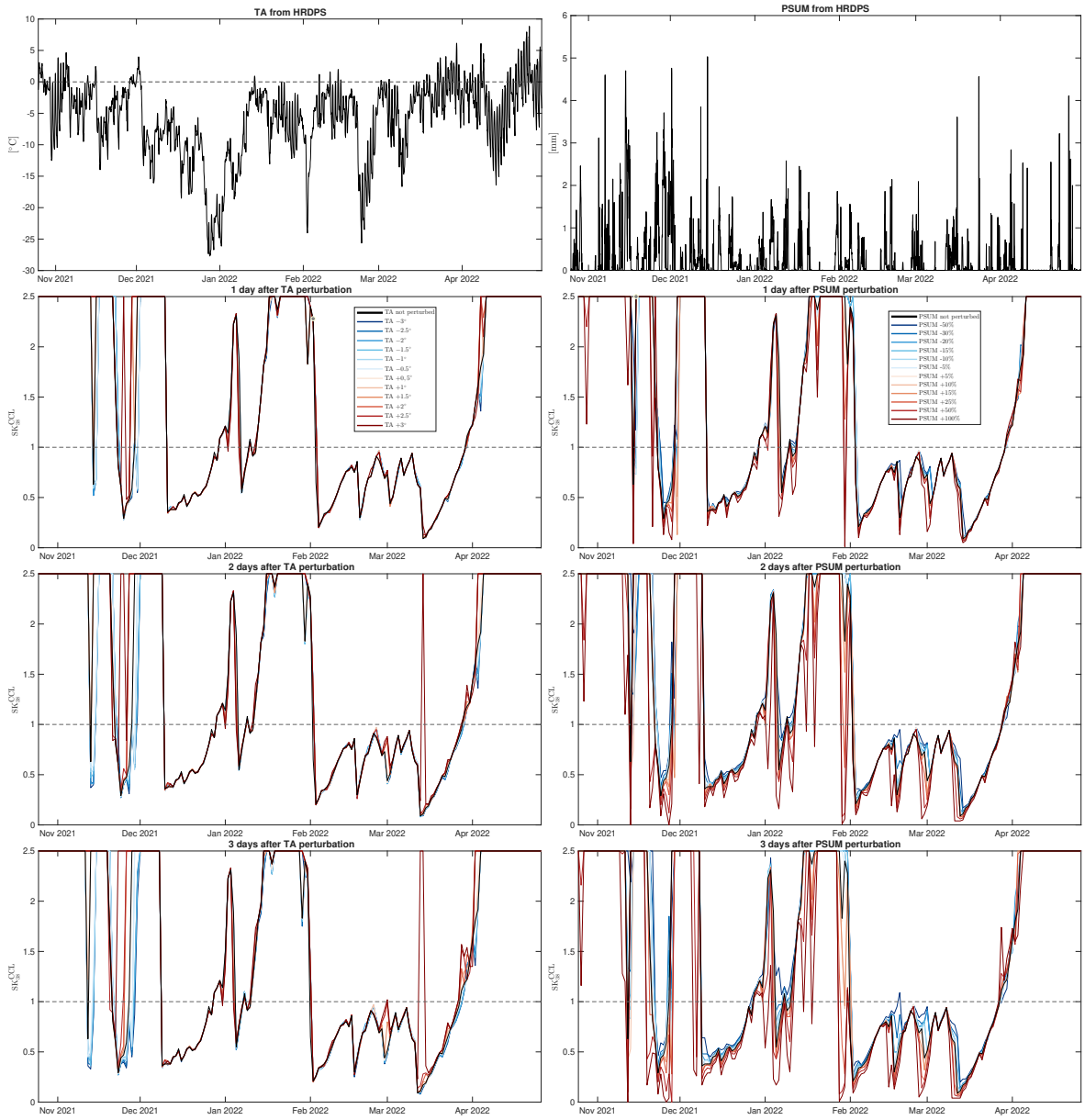


Figure 1: Glacier National Park study site. (top) Seasonal evolution of air temperature and precipitation according to the HRDPS reference forecast. The remaining panels show the impact of air temperature (left column) and precipitation (right column) perturbations on the minimum value reached by the SK_{38}^{CCL} index. Each perturbation was introduced on the day indicated on the x-axis, and the corresponding index values were evaluated one, two, or three days after the perturbation onset.

were just below 0°C. Figure 2 reports the seasonal stratigraphy and stability. Due to the presence of new snow, the SK_{38}^{CCL} index considers the snowpack unstable for few days after December 1. However, as the season progresses, the snowpack becomes stable because no weak layers develop following this snowfall event.

Applying a temperature perturbation of +1.5°C from December 1 causes partial snow melting and the formation of a very thin melt-freeze crust. Although some differences compared to the reference simulation become visible, the SK_{38}^{CCL} index still classifies the snowpack as stable. In contrast, a larger temperature perturbation of +2°C leads to the formation of a thicker melt-freeze crust and faceted crystal weak layers above it, resulting in an unstable snowpack. In particular, initially the index detects the instability associated with the recent snowfall, similarly to the reference simulation. Subsequently, despite the formation of the melt-freeze crust, the snowpack temporarily returns to a stable condition because the overlying slab remains thin and is composed mainly of de-

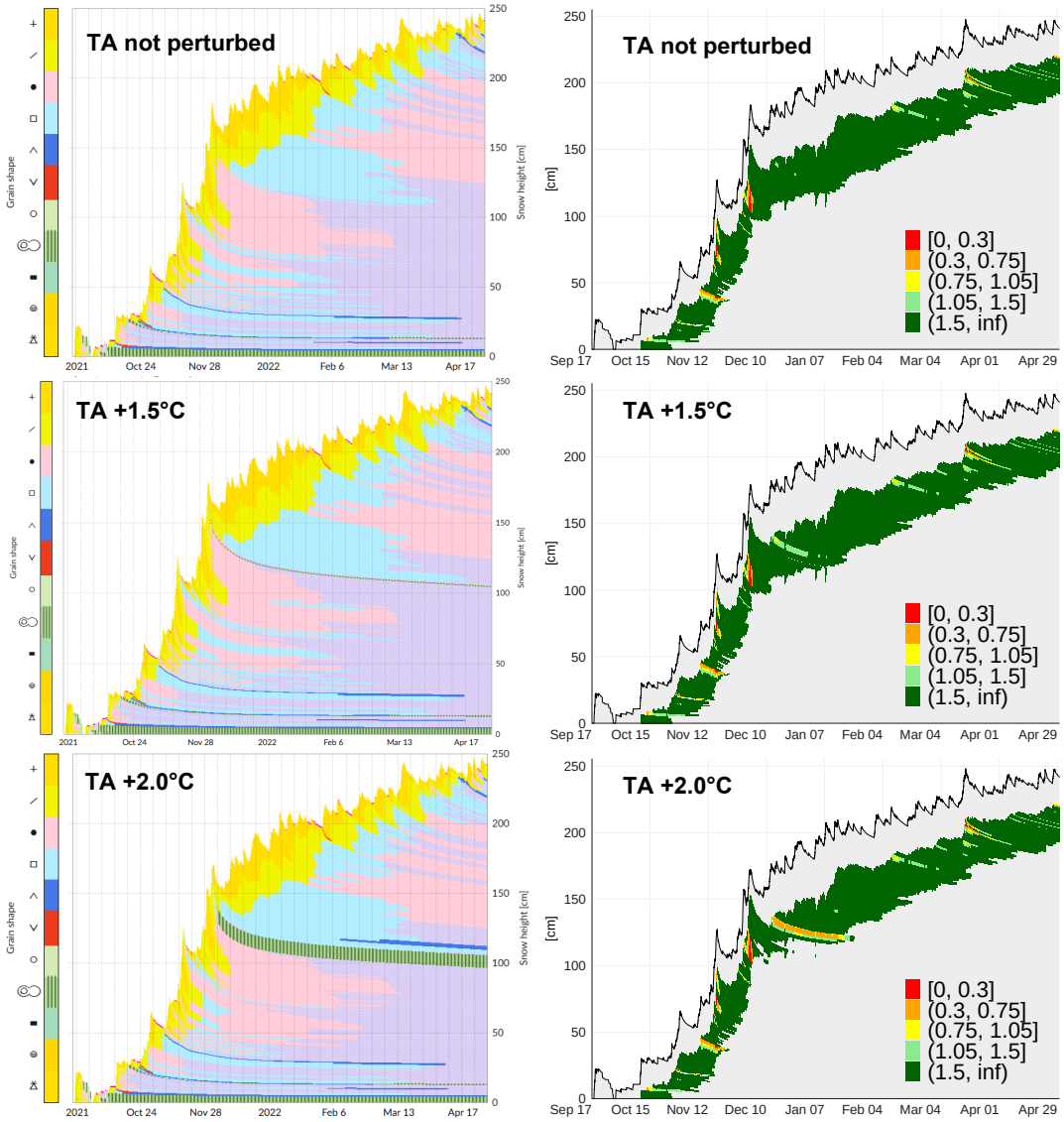


Figure 2: Bow Summit study site. Snowpack stratigraphy (left) and SK_{38}^{CCL} index (right). Red and orange layers indicate unstable conditions, yellow layers intermediate conditions, and green and gray layers stable conditions (Borsotti et al. in preparation). All perturbations were introduced on December 1.

composing and fragmented precipitation particles. Finally, following a subsequent snowfall event, the combination of the melt-freeze crust and the overlying faceted crystal weak layer leads to renewed instability, which persists throughout December and January.

3.3. *Impact of new snow amount perturbations*

Consider the Whistler study site. On January 11, a snowfall event was ongoing and continued for few days. The deterministic snowpack simulation resulted in a stable snowpack for January 12 (see Fig. 3). In particular, a decomposing and fragmented precipitation particles layer was the weakest layer, for which $SK_{38}^{CCL} = 1.60$.

Increasing precipitation by +25 % from January 11 makes the forecasted stability condition uncertain, as the weakest layer becomes a precipitation particles layer with $SK_{38}^{CCL} = 1.02$, very close to the instability threshold. Therefore, the deterministic prediction of a stable snowpack is associated with a positive precipitation uncertainty margin of approximately 25 % (+4.96 mm). As expected, larger increases in precipitation lead to unstable conditions. For instance, a +100 % precipitation perturbation results in $SK_{38}^{CCL} = 0.43$ for a precipitation particles layer. Conversely, negative precipitation perturbations increase snowpack stability. In particular, reductions of -10 % or more shift the weakest layer identified by the SK_{38}^{CCL} index to a rounding faceted particles layer.

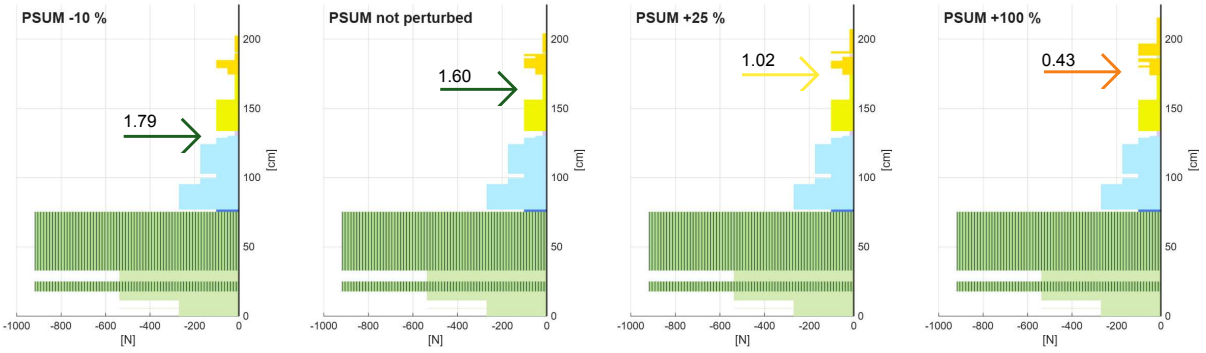


Figure 3: Whistler study site. Snowpack profiles on January 12 at 1 p.m. resulting from different precipitation perturbations applied from January 11 at 2 p.m. Arrows indicate the weakest layer according to the SK_{38}^{CCL} index, while the numbers above them the index's value.

4. DISCUSSION

In this work, we presented a framework to integrate meteorological uncertainty into snowpack and avalanche hazard modeling. In particular, we investigated the effects of perturbations in air temperature and precipitation on snowpack stratigraphy and stability. We showed that even small perturbations can substantially influence the formation and evolution of weak layers, leading either to long-lasting effects throughout the season, such as the formation of melt-freeze crusts and adjacent weak layers, or to shorter-term effects, such as instability associated with increased new snow amounts. Anyway, our results indicate that, during many periods of the season, the snowpack is not particularly sensitive to such perturbations.

The different response of the snowpack to precipitation and temperature perturbations can be explained by the physical processes governing snowpack evolution. Positive precipitation perturbations increase slab loading, generally leading to lower stability (Gaume and Reuter 2017), whereas the influence of air temperature is strongest when temperatures are close to the melting point, where small variations determine whether snow melts or remains preserved and whether precipitation falls as snow or rain (Lehning et al. 2002a). Recall Fig. 1, these mechanisms also explain why the largest perturbation effects were observed at the beginning of the winter season. During this period, frequent snowfall events and temperatures fluctuating around 0°C create conditions in which relatively small changes in meteorological forcing can substantially modify the stratigraphy, influencing the formation of melt-freeze crusts and persistent weak layers (Bartelt and Lehning 2002). Later in the season, although temperatures may still approach the melting point and significant snowfall events may occur, short-lived meteorological perturbations generally produce smaller changes in snowpack stability because the stratigraphy is already well established and potentially dominated by previously formed layers (Lehning et al. 2002b).

These findings suggest that forecast uncertainty is not uniformly distributed throughout the winter season, but instead depends strongly on the prevailing snowpack conditions. Consequently, the value of ensemble-inspired sensitivity analyses is expected to be greatest during periods when the snowpack is actively evolving and is therefore most responsive to meteorological forcing.

4.1. *Operational implications*

Compared with existing ensemble-based frameworks for snowpack forecasting, the proposed methodology requires limited computational resources and relies only on a standard deterministic weather forecast, rather than on a more computationally demanding meteorological ensemble prediction system. Furthermore, the limited number of generated simulations facilitates their direct interpretation by forecasters, without requiring additional methods to summarize or compare ensemble outputs (Viallon-Galinier et al. 2020; Herla et al. 2021; Herla et al. 2022). Finally, because the snowpack is not equally sensitive to meteorological perturbations throughout the season, applying the complete set of perturbations every day may not always be necessary. Instead, perturbations could be selectively applied during periods when forecast uncertainty is expected to have a stronger impact on snowpack evolution. We discuss now two possible operational applications in detail.

The first application concerns the adjustment of snowpack simulations using field observations. Recall Sect. 3.2, the 2021/22 season summary for

Bow Summit reports (Avalanche Canada 2026a):

> [The] December 1 crust became a critical feature of the snowpack, serving as the bed surface for many avalanches. [...] The December 1 crust remained widespread, and storm snow avalanches continued to step down to this layer across the province [during January].

In this case, the deterministic snowpack simulation did not reproduce the formation of this crust and the associated instability, whereas controlled perturbations were able to generate a snowpack consistent with field observations. This demonstrates that even a simplified perturbation framework can be used to improve the agreement between simulated and observed snowpack conditions, similarly to more complex ensemble approaches (Vernay et al. 2015; Lafaysse et al. 2017). For instance, when producing a snowpack forecast for the following day, multiple perturbed simulations could be compared with newly collected field observations to identify the realization that best represents the observed snowpack state. Repeating this process throughout the season could progressively improve the consistency of snowpack simulations, especially in situations where deterministic simulations fail to reproduce relevant snowpack features or, conversely, indicate weak layers that are not observed in the field. Moreover, the same approach could support retrospective analyses by allowing past simulations to be updated when additional observations become available.

A second application concerns the estimation of uncertainty margins around stability assessments. As shown in Sect. 3.3, controlled perturbations provide a simple way to quantify how much meteorological conditions would need to differ from the forecast to alter the simulated stability classification. This information is particularly valuable during periods characterized by large forecast uncertainty or when the snowpack is highly sensitive to meteorological variations. For example, when a deterministic simulation indicates a stable snowpack according to the SK_{38}^{CCL} index, forecasters could evaluate which deviations in temperature or precipitation would instead lead to instability. This application relies specifically on controlled forcing biases, since random perturbations would not provide information on the direction and magnitude of the meteorological changes required to trigger a transition in stability. Interestingly, the avalanche danger level issued for Whistler on January 12 was 3 (Avalanche Canada 2026a), indicating unstable conditions. While such instability was not captured by the deterministic simulation, it was reproduced by the proposed ensemble-inspired approach.

4.2. Limitations

We emphasize that the proposed approach cannot be used to derive probabilistic statements about snowpack stability. The main limitation is that the applied perturbations are not defined in a probabilistic framework. As a consequence, the resulting ensemble does not represent a calibrated probability distribution of possible snowpack states, but rather a set of sensitivity experiments. To obtain meaningful probabilistic estimates of instability, it would be necessary to assign probabilities to each perturbation (Raftery et al. 2005). Without this, the ensemble spread can only be interpreted as a measure of sensitivity to input uncertainty, rather than as a probability of instability.

5. CONCLUSIONS

This pilot study shows that even relatively small meteorological perturbations can substantially affect simulated snowpack structure and stability. In particular, our results suggest that precipitation is often the dominant driver of changes in snowpack stability, whereas temperature becomes especially critical near 0°C. These findings highlight that deterministic snowpack simulations may fail to capture important instability signals when meteorological uncertainty is not explicitly considered. To address this limitation, we presented a framework based on controlled perturbations of air temperature and precipitation to explore an ensemble of possible snowpack evolutions. The proposed approach is intended as a practical sensitivity framework that can support operational avalanche forecasting. Its main advantage is that it remains computationally and analytically simple enough to be integrated into existing forecasting workflows. Two operational applications appear particularly promising: improving the alignment of snowpack simulations with field observations and estimating uncertainty margins around stability assessments.

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